Online distributed motion planning for multi-vehicle systems using receding-horizon ADMM

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This work focusses on motion planning for multi-vehicle systems, which is in general formulated as optimization problem (1). This problem searches for each vehicle's time-dependent motion trajectory $x_i(\cdot)$. Optimal trajectories are obtained by minimizing the sum of all vehicle objectives, that steer them to their target state $x_{T,i}$, and respect local vehicle constraints, such as initial and terminal state constraints, kinematic and dynamic limitations and collision avoidance constraints, described by a set $\mathcal{X}_i$. Each vehicle has several neighbors, denoted by the set $\mathcal{N}_i$ and an interaction constraint g_{ij} implies a relation between the trajectory x_i and x_j of respectively an agent i and its neighbor j. This relation can be for example attaining a formation or meeting at a destination position. The trajectories are parameterized as splines as they allow a representation with a limited number of variables and enable guaranteed constraint satisfaction with a finite set of constraints.

$$\begin{aligned} \underset{\forall i:\, x_i(\cdot)}{\text{minimize}} \quad & \sum_{i=1}^{N} \int_0^T \|x_i(t) - x_{T,i}\|_1 dt \\ \text{subject to} \quad & x_i(t) \in \mathcal{X}_i \\ & g_{ij}(x_i(t), x_j(t)) = 0, \quad \forall j \in \mathcal{N}_i \\ & \forall t \in [0,T], \quad \forall i \in \{1, ..., N\}\,. \end{aligned} \tag{1}$$

In order to distribute the computations among the agents, problem (1) is decoupled using the Alternating Direction Method of Multipliers (ADMM) [1]. This results in an iterative solution strategy where in each iteration every agent solves only a local motion planning problem, considering its own constraints and objective. By communicating with its nearest neighbors, it is possible to incorporate the neighbors' intentions. This way, the ADMM iterations converge towards optimal motion trajectories where both the local vehicle constraints and the global interaction constraints are satisfied.

In order to cope with disturbances or a dynamic environment, a receding-horizon version of ADMM is proposed. The trajectories are reoptimized in a receding-horizon fashion and each trajectory update only one ADMM iteration is executed. In this way, the problem converges while the vehicles are heading towards their destination. Each update a new time horizon and corresponding spline basis is defined. Because an ADMM iteration requires the information of trajectories of the previous iteration, their future part is first expressed in the new basis before introducing them to the next iteration. Currently, the authors are working on a stability proof for this iteration scheme applied to convex problems.

The proposed algorithm is implemented as part of a general spline-based motion planning toolbox[1], which also contains many numerical examples considering formation and rendez-vous problems for different linear as well as non-linear vehicle models. In the near future the proposed approach will be validated experimentally on a fleet of in-house developed mobile platforms.

References

[1] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, Distributed optimization and statistical learning via the alternating direction method of multipliers, *Foundations and Trends® in Machine Learning*, vol. 3, no. 1, pp. 1-122, 2011.

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[1] https://github.com/meco-group/omg-tools